The Structure of Firm R&D and the Factor Intensity of Production*

by

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Abstract

This paper studies the influence of the structure of firm R&D, industry R&D spillovers, and plant level physical capital on the factor intensity of production. By the *structure* of firm R&D we mean its distribution across states and products. By *factor intensity* we mean the cost shares of variable factors, which in this paper are blue collar labor, white collar labor, and materials. We characterize the effect of the structure of firm R&D on factor intensity using a Translog cost function with quasi-fixed factors. This cost function gives rise to a system of variable cost shares that depends on factor prices, firm and industry R&D, and physical capital.

The paper turns to estimation of this system using a sample of plants owned by chemical firms, which nevertheless covers a variety of manufacturing industries. We find that total firm R&D, industry R&D spillovers, and plant level physical capital are factor biased towards labor as a whole, and factor saving in materials. None of these three factors *consistently* increase the factor intensity of white collar workers relative to blue collar workers. Since white collar workers are the more skilled of the two grades of labor, none of these factors is strongly associated with *skill bias*.

When we turn to the structure of firm R&D, we find that the strongest effect of firm R&D on the factor intensity of white collar workers occurs when the R&D is conducted in the same product area as the plant. Indeed, the skill bias effect of firm R&D in the same product dominates all other variables, implying that skill bias is technologically "localized" within firms. All told, the findings suggest that skill bias is governed by *portions* of the firm's R&D program that are targeted on particular plants, rather than transmitted through capital or by general firm and industry know-how.

KEYWORDS: Cost and Production Functions, Technological Change, R&D, Factor Bias, Factor Intensity, Capital-Skill Complementarity

JEL Classification: D21, O32, L23, J23

I. Introduction

The influence of Research and Development (R&D) on productivity, cost, and the factor intensity of production has been an important part of the economics of industry since at least the time of Marshall[1]. However, it is only recently that economists have explored the empirical implications of firm R&D and industry R&D spillovers for the structure of cost and production.

Studies have been carried out at both the firm and industry levels. Industry level studies include Bernstein and Nadiri (1988), which finds strong cost reducing and factor intensity effects of own R&D and inter-industry R&D spillovers. Using science-based measures of R&D, Adams (1990) finds that lagged own and inter-industry spillovers are a key determinant of productivity.

A sampling of studies at the firm level include Jaffe (1986), who explores implications of firm R&D and R&D spillovers for firm productivity and stock market value. Bernstein and Nadiri (1989) assess the role of firm R&D and industry spillovers in the context of dynamic cost minimization. They find that own R&D and R&D spillovers reduce cost and that spillovers are a substitute for firm investments in R&D. Mairesse and Hall (1995, 1996) explore the relationship between R&D and productivity in panels of French and American manufacturing firms.

A related strand of literature emphasizes the complementarity between capital, technology, and skill. Examples of this literature include Griliches (1969), Bound and Johnson (1992); and Berman, Bound, and Griliches (1994). This literature finds that capital and technology are skill using, but factor saving in unskilled labor.

This paper examines the role of the structure of firm R&D, of industry R&D spillovers,

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[1] Alfred Marshall, **Principles of Economics**, 8th ed. (1920), Book IV, Chapters IX-XI. In these chapters Marshall discusses the role of machinery and disembodied knowledge in the determination of efficient firm size. He regards the proliferation of types of machinery as a change in technology that favors larger firms. In contrast he views external economies, which he identifies with knowledge spillovers, as a factor favoring smaller firms.

and of plant level capital on factor intensity and skill bias at the plant level[2]. By the *structure* of firm R&D we mean its distribution across states and products. By *factor intensity* we mean the cost shares of variable factors, which include blue collar workers, white collar workers, and materials[3]. S*kill bias* is defined as an increase in the cost share of more skilled white collar workers relative to that of less skilled blue collar workers, due to technological change and capital formation.

By utilizing information on the structure of firm R&D, industry R&D, and physical capital, we are able to shed light on three issues. First, we are able to separate the effects of different types of R&D and capital on factor intensity. Second, since we break up firm R&D into its various components while holding constant a measure of industry spillovers, we can distinguish the effects of different types of firm R&D on factor intensity. And third, since our data report factor intensities of blue and white collar workers, and white collar workers are more skilled, we can identify skill biases due to the different forms of R&D and capital.

Results from this investigation are as follows. Almost without exception we find that firm and industry R&D and physical capital are factor biased towards labor, and factor saving in materials. However, none of these factors *consistently* raise the factor intensity of white collar workers relative to blue collar, so that none can be said to be strongly associated with *skill bias.*

We uncover the strongest effects of firm R&D on skill bias when we examine the structure of firm R&D. In particular, firm R&D in the same product as the individual plant increases the cost share of white collar labor relative to the blue collar share. Firm R&D in the same state is skill biased, but the effect is fragile, and disappears in the long run. Since white collar workers are more skilled than blue collar, the effect of firm R&D in the same product implies the skill bias is "localized" within firms. On the whole, our findings suggest that skill bias is governed by *portions* of the firm's R&D that are targeted on individual plants, rather than

[2] Adams and Jaffe (1996) explore the implications of the structure of firm R&D for plant level total factor productivity, but they do not consider factor intensity and skill-bias given their factor-neutral framework.

[3] Throughout this paper "blue collar" refers to production workers, while "white collar" refers to non-production workers. "Materials" on the other hand refers to the aggregate of materials, energy, and services.

transmitted through capital or by general firm and industry know-how.

The paper is organized as follows. Section II models a particular specification of the Translog cost function with quasi-fixed inputs. We use this cost function to develop a system of cost shares that is influenced by factor prices, R&D, and physical capital. Section III describes the data, which relate to the chemicals industry. These are a combined sample drawn from several Census surveys covering production, cost, and R&D in manufacturing. Section IV presents the findings, starting with descriptive statistics, and continuing with the cost share systems. Section V provides a discussion and overview. Section VI concludes and discusses extensions of the research.

II. Cost and the Factor Intensity of Production

Our empirical analysis pivots off of a quasi-fixed Translog cost function for plant level costs[4]. We use the quasi-fixed form of cost because of the importance of adjustment costs for R&D and physical capital. In this paper, owing to the design of the underlying surveys, the cost function depends on prices of three variable inputs: blue collar labor, white collar labor, and materials. Plant level costs depend besides on quasi-fixed inputs consisting of parent firm R&D, spillovers of industry R&D, and the plant level stock of physical capital.

The key advantage of our data is the availability of a *structure* of the parent firm's R&D by state and product, and we specify the cost function accordingly. This structure plays two roles in our analysis. First it allows us to study "localization," or the differential effect of distant and nearby firm R&D on cost. We consider three specifications of firm R&D: total R&D, R&D in the same state as the plant versus R&D in other states, and R&D in the same product area as

[4] Christensen, Jorgenson, and Lau (1973) introduced the Translog cost function. Brown and Christensen (1981) developed the Translog cost function with quasi-fixed inputs. Also see Berndt (1990) for an overview of Translog estimation.

the plant versus R&D in other product areas[5].

The second role played by the structure of the parent firm's R&D, specifically its distribution across products, is that it captures technological similarity between one firm and others. This allows us to map the R&D of other firms to the firm in question according to the similarity of product distributions with other firms: see the discussion of (10) below.

The quasi-fixed Translog cost function allows considerable latitude in the specification of substitution possibilities, subject to changes in firm R&D, in industry R&D spillovers, and in the physical capital of the plant. Dropping time subscripts the cost function of a plant is

$$\begin{aligned} \ell n\, C = \boldsymbol{a}_0 + \sum_h \sum_{i=B,W,m} \boldsymbol{a}_{hi}\, \mathrm{D_h}\, \ell n\, w_i + \sum_{i=B,W,m} \sum_{j=B,W,m} \boldsymbol{b}_{ij}\, \ell n\, w_i\, \ell n\, w_j + \\ \boldsymbol{b}_q\, \ell n\, q + \sum_{i=B,W,m} \boldsymbol{b}_{\mathrm{iq}}\, \ell n\, w_i\, \ell n\, q + \boldsymbol{b}_R\, \ell n\, R + \sum_{i=B,W,m} \boldsymbol{b}_{\mathrm{iR}}\, \ell n\, w_i\, \ell n\, R\, + \\ \boldsymbol{b}_S\, \ell n\, S + \sum_{i=B,W,m} \boldsymbol{b}_{\mathrm{iS}}\, \ell n\, w_i\, \ell n\, S + \boldsymbol{b}_K\, \ell n\, K + \sum_{i=B,W,m} \boldsymbol{b}_{\mathrm{iK}}\, \ell n\, w_i\, \ell n\, K. \end{aligned} \tag{1}$$

Throughout the paper $i{=}B,W,m$ refers to blue collar labor, white collar labor, and materials, $\ell n\, C$ is the log of total cost, $\ell n\, w_i$ is the log of the price of the ith variable input, D_h is an industry dummy variable that equals 1 if the plant is in the hth industry group and 0 otherwise, and $\ell n\, q$ is the log of plant output. The terms $\ell n\, R$, $\ell n\, S$, and $\ell n\, K$ are logs of firm R&D, the log of the industry R&D spillover, and the log of plant level physical capital. Firm R&D and its effects $\boldsymbol{b}_R$ and $\boldsymbol{b}_{iR}$ are vectors in those cases where we break up firm R&D into a series of components.

Industry effects are captured by the first sum on the right of the cost function. The interactions of the industry dummies with the factor prices allow the cost shares to differ between industries, an essential feature of our data. The sum over products of the log input prices takes own and cross substitution effects of the factor prices into account. For simplicity we treat these cross price effects as the same across industries.

[5] We are unable to study the effects of firm R&D classified by *both* state and product, since the data are collected

The parameters β_q, β_R, β_S, and β_K measure the effect on total cost of the log of plant output, the log of firm R&D, the log of the industry R&D spillover, and the log of plant level capital stock. Remaining terms are interactions between logs of the factor prices and the log of output, firm R&D, the industry spillover, and plant level capital. These terms take account of the effects of the quasi-fixed inputs on the variable factor. For convenience we ignore second order own and cross effects of output and the quasi-fixed factors.

Since cost is homogeneous of degree one in prices, the following restrictions hold in (1):

$$\begin{aligned}
&\sum_{i=B,W,m} \alpha_{hi} = \sum_{h} \sum_{i=B,W,m} \alpha_{hi} D_h = 1, \\
&\sum_{i=B,W,m} \beta_{ij} = \sum_{j=B,W,m} \beta_{ij} = \sum_{i=B,W,m} \sum_{j=B,W,m} \beta_{ij} = 0, \\
&\sum_{i=B,W,m} \beta_{iR} = 0, \quad \sum_{i=B,W,m} \beta_{iS} = 0, \quad \sum_{i=B,W,m} \beta_{iK} = 0,
\end{aligned} \tag{2}$$

The homogeneity restrictions (2) allow normalization of (1) by one of the factor prices[6]. Using materials price (w_m) for this purpose we reach the normalized Translog cost function,

$$\begin{aligned}
\ell n\,(C_i / w_m) = {} & \alpha_0 + \sum_{h} \sum_{i=B,W} \alpha_{hi} D_h \,\ell n\,(w_i / w_m) \\
& + \sum_{i=B,W} \sum_{j=B,W} \beta_{ij} \,\ell n\,(w_i / w_m)\,\ell n(w_j / w_m) + \beta_q \,\ell nq \\
& + \beta_R \,\ell nR + \sum_{i=B,W} \beta_{iR} \,\ell n\,(w_i / w_m)\,\ell nR + \beta_S \,\ell nS \\
& + \sum_{i=B,W} \beta_{iS} \,\ell n\,(w_i / w_m)\,\ell nS + \beta_K \,\ell nK \\
& + \sum_{i=B,W} \beta_{iK} \,\ell n\,(w_i / w_m)\,\ell nK,
\end{aligned} \tag{1$'$}$$

in which the two relative prices, for blue and white collar labor, are w_B / w_m and w_W / w_m.

By Shephard's lemma the cost share s_i for input i is given by $\partial\,\ell n\,(C/w_m)/\partial\,\ell n\,(w_i/w_m) = s_i$. Differentiating (1′) with respect to the relative price of blue and white collar labor and using this result yields the following system of cost shares:

by state or product but not by both, owing to the complexity of the data collection effort.

[6] To see this, use $\alpha_{hm} = 1 - \alpha_{hW} - \alpha_{hB}$, $\beta_{mi} = -(\beta_{Wi} + \beta_{Bi})$, and so on from (2) to arrive at (1′).

$$s_{Bl} = \alpha_{Bl} + \sum_{i=B,W} \beta_{Bi} \ell n\,(w_i/w_m) + \beta_{Bq} \ell n\, q + \beta_{BR} \ell n\, \mathrm{R} + \beta_{BS} \ell n\, S + \beta_{BK} \ell n\, K + u_B$$

$$s_{Wl} = \alpha_{Wl} + \sum_{i=B,W} \beta_{Wi} \ell n\,(w_i/w_m) + \beta_{Wq} \ell n\, q + \beta_{WR} \ell n\, \mathrm{R} + \beta_{WS} \ell n\, S + \beta_{WK} \ell n\, K + u_W \tag{3}$$

where l is the lth industry and u_B, u_W are random errors. Note that the intercepts of (3) are industry-specific. Also, we have dropped the materials equation because cost shares sum to unity and parameters for the materials cost share are implied by the parameters of the white and blue collar equations. For future reference note that the parameters measure sensitivity of the cost shares with respect to one percent changes in the right hand side variables.

One can test (3) for homotheticity of the structure of production, or that is to say, independence of the cost shares from the levels of output and the quasi-fixed factors. This amounts to testing the following linear restrictions for each equation in (3):

$$\beta_{iq} = -(\beta_{iR} + \beta_{iS} + \beta_{iK})\,. \qquad \text{(i=B,W)} \tag{4}$$

Acceptance of these restrictions implies that the cost shares take the form

$$s_{Bl} = \alpha_{Bl} + \sum_{i=B,W} \beta_{Bi} \ell n\,(w_i/w_m) + \beta_{BR} \ell n\,(R/q) + \beta_{BS} \ell n(S/q) + \beta_{BK} \ell n\,(K/q) + u_B$$

$$s_{Wl} = \alpha_{Wl} + \sum_{i=B,W} \beta_{Wi} \ell n\,(w_i/w_m) + \beta_{WR} \ell n\,(R/q) + \beta_{WS} \ell n\,(S/q) + \beta_{WK} \ell n\,(K/q) + u_W \tag{5}$$

Now the cost shares depend on the ratios, or *intensities*, of firm R&D, the R&D spillover, and capital to output. Systems (3) and (5) form the core of the empirical work reported below.

III. Nature of the Data

A. Construction of the Variables

The data derive from various Census surveys of chemical firms and manufacturing plants owned by these firms. However, the plants themselves are by no means limited to chemicals, since chemical firms produce a variety of goods that include most of manufacturing. Chemicals are easier to study than most other high technology sectors because cost, production, and R&D data from the industry tend to be above average in quality. Chemical plants are older, larger, and better documented in the Census of Manufacturing than most other plants. Since the industry is mature, the R&D survey measures R&D by state with reasonable accuracy. Furthermore, the survey reports R&D by product with less error than seems to be the case for most industries. This is because there are clear distinctions between technologies in chemical industries that follow the applied product breakdown in the R&D survey. Thus with some confidence we can construct pools of firm and industry R&D that follow the applied product fields, even though R&D pools fail to coincide with these fields in most industries[7]. A final reason why the data are restricted to chemicals is the time-consuming nature of the calculations required to merge the different files, to check the data for imputations and data errors, and to create the variables.

The data cover the period 1974-1988. They begin in 1974 because of limitations on earlier *R&D* data. Data before 1972 are not available at Census, while sample sizes for 1972 and 1973 are smaller than in later years. The data end in 1988 because stocks of plant level *physical* capital have not been collected since by the Annual Survey of Manufactures (ASM). Thus capital stocks are missing after 1988, though they are needed for the cost function estimates. For all these reasons the time period is limited to 1974-1988.

Before exclusions the database consists of 1,150 chemical firm-years and 21,500 plant-years. These statistics correspond to roughly 80 chemical firms per year and 1,400 chemical plants per year, more in earlier years and less later on, when sample sizes decrease in the

[7] Consider machinery and electronics. R&D spills over between different branches of machinery and electronics, which use related technologies, so the R&D pools exceed product R&D to an unknown extent.

manufacturing surveys. The data contain about 18 plants per firm in an average year.

Exclusions reduce the sample from the original 21,500 observations. Sample losses are mostly due to requirements that firm level R&D data exist, but also from requirements that the plant level cost and production data be non-missing and meet other criteria that are explained below. After allowance is made for bad and missing data, about 18,500 observations remain. The condition that firm R&D data exist five years in the past cuts this sample almost in half to approximately 9,500 observations.

The chemical industry data employed in this paper are a combination of six data sources. The sources include cost and production data on *manufacturing* plants of chemical firms in the Annual Survey of Manufactures and the Census of Manufactures, known as the Longitudinal Research data base (LRD). They also include firm, state and firm, and product and firm R&D data from the Census R&D survey. In addition we use data on R&D at the state and firm level that is conducted in separate research laboratories. These data are drawn from the Survey of Auxiliary Establishments conducted in the three Census of Manufacturing years 1977, 1982, and 1987 that span our time period[8]. For the purpose of constructing relative prices of white and blue collar workers required by the system of Translog cost shares (see (3) and (5) above), we employ data on state and industry mean weekly wages of production workers from the Bureau of Labor Statistics (BLS). We draw on two data sources for the deflators needed for materials, output, investment, and capital. The first is the four digit manufacturing industry database of the National Bureau of Economic Research (see Bartelsman and Gray (1996)). This provides deflators for materials, output, and investment. The second source is the Bureau of Economic Analysis (BEA) capital stock data, which contain deflators and depreciation rates for capital

[8] The data on auxiliary R&D by firm and state are a sample, not a complete census of such R&D, so that we cannot directly compare auxiliary R&D by state with firm R&D by state from the LRD survey.

stocks of equipment and structures.

The LRD is sufficient for the purpose of calculating the cost shares on the left of (3) and (5). However, the LRD lacks much of the data needed to construct right hand side variables. It lacks deflators and rates of depreciation needed to calculate the real stock of physical capital, which are provided by the BEA and NBER data. Labor prices, output deflators, materials prices, and the R&D variables are likewise missing from the LRD. The BLS data combined with the LRD provide labor prices and deflators. The NBER data include deflators for output, investment in capital, and materials prices. The R&D data provide firm R&D and their distribution by state and product, which are needed for stocks and flows of firm and industry R&D.

In constructing the final data set we tried to match every observation in the LRD, the Census R&D data, and the Survey of Auxiliary establishments data that met certain criteria for data quality[9]. In the case of the R&D we required that data *almost always* exist on research expenditures by state and product. We required that the R&D data be real and not imputed and that the state and product field components approximately add to totals. In the few cases where the data failed to exist we required that data exist in adjacent years so we could interpolate over missing values[10].

We calculate expenditures for blue and white collar labor and the materials aggregate as follows. Blue and white collar expenditures are available in the LRD in the form of annual wages and supplementary labor costs[11]. Materials are the sum of cost of materials and parts, cost

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[9] We say attempted, because firm ids in the R&D surveys are not updated with ownership changes as they are in the LRD. We achieved a 95% match rate for R&D firms in census years and a 74% match rate in ASM years, reflecting the exclusion of small plants in ASM years.

[10] This criterion, combined with the appearance and disappearance of firms from the ASM, has the effect of introducing holes or perforations in the merged data. Hsiao (1986), Chapter 8 contains a discussion of econometric methods for dealing with perforated data, though they are of limited use. The perforations make it quite difficult to apply panel data econometrics, since these require balanced panels to be practicable: see Baltagi (1995), Ch. 8.

of fuels not including electricity, cost of contract work, and cost of purchased electricity. Materials expenditures and labor costs sum to total variable costs, so cost shares for blue and white collar labor are labor expenditures divided by total variable costs. Since variable cost shares sum to one, we drop the materials share equation from the estimation procedures.

Following (3) and (5) we compute prices of white and blue collar labor relative to materials. We calculate the labor prices at the *state and industry* level. As a result we retain "local labor market" effects in the labor prices and improve their robustness in the presence of time trend[12]. Our method is to match unpublished average weekly earnings of production workers by state and industry from the Bureau of Labor Statistics (BLS) with the state and industry groups in the sample for each year[13]. The BLS weekly wage for production workers by state and industry provides our estimate of the blue collar labor price.

Having obtained an estimate of the blue collar weekly wage it remains to estimate the white collar weekly wage by state and industry. Weekly earnings of white collar workers are not available in the BLS data alone. Instead we estimate white collar weekly wages using both the LRD and the BLS data. We calculate state mean average *annual* earnings of white and blue collar workers for each year using our LRD data on chemical firms, thereby providing state level earnings that are specific to chemicals. Annual earnings are the only pay measure for both types of labor in the LRD. Our estimate of white collar weekly earnings is then

$$w_{wn} = w_{bl} \times \frac{E_{wh}}{E_{bl}}, \tag{6}$$

where E_{wh} and E_{bl} are annual earnings of white and blue collar earnings in a given state from the

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[11] It was necessary to distribute supplementary labor costs between white and blue collar labor in the same proportion as their shares in wage costs.
[12] The factor prices are insensitive to the inclusion of time trend or time dummies in the tables presented below.
[13] The BLS data are in electronic form. These data underlie the BLS series on average weekly wages of production workers by state in **Employment and Earnings**.

LRD. Equation (6) requires the ratio of weekly earnings of white and blue collar workers in a given industry and state to be in the same ratio as annual earnings of the two groups of workers in the same state irrespective of industry. The reason is that sample sizes are too small to break up the LRD data by both industry and state. However, white collar *weekly* earnings in an industry and state do vary relative to the state mean ratio of annual earnings E_{wh} / E_{bl} according to blue collar weekly earnings, which are industry- and state-specific. The estimate in (6) is the best we have of white collar weekly earnings in an industry and state.

The next step in the calculation of the factor prices expresses blue and white collar labor weekly earnings in 1987 dollars. We divide w_B and w_W by their average over *all* industries and states in 1987. This method of deflation retains state and industry variation in the data while expressing weekly earnings relative to 1987 values, consistent with the treatment of our other deflators for shipments, materials, investment, physical capital, and R&D. Finally we divide the deflated labor prices by the price of materials in 1987 dollars taken from the NBER four digit industry database[14]. These calculations provide estimates of the relative blue and white collar labor prices in 1987 dollars. In the notation of (3) and (5) these are w_B/w_m and w_W/w_m.

Equations (3) and (5) also require stocks of R&D and physical capital as explanatory variables. We construct stocks of plant level physical capital following Lichtenberg (1992). In the initial year of the time series for any plant we deflate gross book values of equipment and structures separately using the BEA's two digit deflators for each type of capital[15]. Deflators are provided by the ratio of industry net capital stock in 1987 dollars, to industry gross capital in

[14] Materials prices are not available at the state and industry level. To see why, consider that the price of materials is a weighted average of the price of shipments using an input-output table. To our knowledge, there are no input-output tables that incorporate state as well as industry in their design.

[15] We thank John Musgrave of BEA for the unpublished industry deflators for capital.

historical dollars. Attaching year subscript t, initial capital stock is

$$C_{kit} = GBV_{kit} \times \frac{NCC_{kjt}}{GHC_{kjt}}, \tag{7}$$

where C_{kit} is real capital stock of type k (equipment or structures) in plant i, GBV_{kit} is gross book value of the plant in historical dollars, NCC_{kjt} is net capital stock of type k in the jth industry in constant 1987 dollars, and GHC_{kjt} is gross capital stock of type k in the jth industry in historical dollars. For succeeding years in the time series of each plant we apply the perpetual inventory formula separately for equipment and structures,

$$C_{kit} = I_{kit} + (1 - d_{kjt}) \times C_{kit-1}, \tag{8}$$

in which C_{kit-1} is real capital stock of type k (equipment and structures) of the ith plant from year t-1, d_{kjt} is the BEA depreciation rate for the type k in the jth two digit industry of the plant, and I_{kit} is real gross investment in equipment and structures in the ith plant in 1987 dollars. Real investment I_{kit} is nominal investment divided by the NBER investment deflator in 1987 dollars. Bailey, Campbell, and Hulten (1992) found that this method explained plant productivity as well as the perpetual inventory method applied to the entire investment stream.

In addition to physical capital the model emphasizes the importance of the firm's stock of knowledge and the industry pool of knowledge for the structure of production. We introduce the flow of firm R&D, or alternatively the partial stock of firm R&D as proxies for the firm's accumulated stock of knowledge. The flows and stocks differ if firms vary their R&D programs over time. However, there is substantial persistence in the R&D programs of individual firms so stock and flow estimates should be similar[16]. To test this, in addition to the flow of firm R&D we calculate a partial stock of its R&D over the *previous* five years:

$$RDK_t = \sum_{i=1}^{5} (1 - d_R)^i RD_{t-i}, \tag{9}$$

[16] See Griliches, ed. (1984), Hall (1995), and Mairesse and Hall (1996) for more on this point.

where the depreciation rate $\boldsymbol{d}_R$ is taken to be fifteen percent per year[17]. The stock of R&D is restricted to the previous five years in order to limit attrition of the sample. We compute flows and stocks for total R&D, R&D in the same state as the plant, and in other states; and R&D in the same product area as the plant, and in other product areas.

We construct the estimate of the industry R&D spillover using the "technological proximity" method of Jaffe (1986). The spillover is defined as

$$S_{it} = \sum\nolimits_{j \neq i} \boldsymbol{r}_{\mathrm{ij}} \mathrm{R}_{\mathrm{jt}} \tag{10}$$

where $\boldsymbol{D}_{ij}$ is the uncentered correlation between the shares of R&D of firms i and j distributed in each of thirty-two product fields in the R&D survey, and R_{jt} is the flow of total R&D of firm j.

Unlike firm R&D, we cannot calculate an R&D spillover stock. If we were to recalculate the spillover over each of the five years in the past, its effects would not be for the same firms. Instead it would be influenced by the appearance and disappearance of firms from the R&D survey, an inescapable feature of the data. It is not possible to calculate a pure spillover *stock* in our data because the spillover pertains to different firms depending on the sample year.

B. Description of the Data

Tables 1 through 3 report summary statistics. Table 1 shows the distribution of the labor and capital cost shares by the number of plants in the firm, a measure of firm size. Table 2 displays the distribution of the plants by industry group and cost shares by industry group[18]. Table 3 reports means and standard deviations of the R&D variables.

Table 1 shows that the share of white collar labor declines as the number of plants

[17] See Griliches and Lichtenberg in Griliches, ed. (1984) among others for evidence on the rate of obsolescence to firm R&D.
[18] As one would expect of this industry, over half of the plants are concentrated in seven localities: California, Illinois, New Jersey, New York, Pennsylvania, Ohio, and Texas.

increases. The fall in the white collar share is probably an artifact of centralization of administrative personnel in larger firms, and not a true decline in white collar employment. Since the data are limited to manufacturing plants we do not observe centralized employment. Thus we introduce the log of the number of firm plants as a control for firm size[19].

Table 2 presents sample sizes and mean labor cost shares by industry group. Despite the fact that parent firms are classified in chemicals, the plants span manufacturing. Approximately two thirds are in the core chemical, petroleum, and rubber industries. Many of the rest are clustered in other high technology industries: machinery, electrical equipment, and instruments; while still others are in food processing and metals fabrication. Industry dummies used in the empirical work follow the groups listed in Table 2.

Table 2 shows that average cost shares vary a great deal by industry. This pattern justifies the industry-specific intercepts of (3) and (5). The share of blue collar labor varies from 0.09 to 0.25 while the white collar share ranges from 0.03 to 0.21. Not surprisingly, the white collar share is highest in R&D intensive industries: drugs and agricultural chemicals, machinery, electrical equipment, and instruments. The blue collar share is lowest in materials processing industries such as food; soaps, paints, and miscellaneous chemicals; and petroleum refining.

According to Table 3, Panel A, the average firm in the sample spends 164 million R&D dollars per year. Average R&D performed in a state is 13 million dollars. Average R&D conducted in a product is 24 million dollars. These numbers imply that the average firm conducts R&D in roughly ten states and five products[20]. The mean industry R&D spillover is estimated to be about 1.2 billion dollars. The pool of industry R&D is eight times larger than firm R&D, though the standard deviations reveal an enormous variation in this and other ratios.

[19] A related variable, the log of the number of employees in the firm, performs similarly. When it is entered along with the log of the industry number of plants in the cost share equations, the two variables share the effect of the number of plants. Estimates of other effects are about the same as those reported below.

[20] Some R&D is not assigned to a particular state or product, perhaps because it is spent on locations or products outside the range of the survey. One fourth of total R&D could not be assigned. Thus the average firm spent 123 million on known states or products out of 164 million. Division of this number by 12 and 23 million yields the

Panel B displays similar statistics for the R&D stock data. The stock sample is about half the flow sample and contains approximately 9,500 observations. Firms in Panel B are larger performers of R&D than in Panel A. This is consistent with the fact that the R&D survey tracks larger firms with higher probability over longer periods. Since the R&D data are five year stocks in Panel B, the amounts are almost five times larger than the flow data in Panel A. The R&D spillover is also larger, reflecting the larger size of Panel B firms.

IV. Empirical Findings

A. Choice of Functional Form for the Cost Shares

We begin with a discussion of choice of functional form. Earlier we pointed out that if each of the cost share equations in (3) satisfied the following restriction,

$$b_{iq} = -(b_{iR} + b_{iS} + b_{iK}), \qquad \text{(i=B,W)}$$

then the quasi-fixed factors could be expressed as ratios to output, and the cost function would be homothetic, yielding (5). Table 4 reports homotheticity tests for the cost share system. The table includes both plant level and state and firm level findings. Panel A reports findings for flows while Panel B reports results for stocks, a pattern we follow for the rest of the paper.

Equations 4.1 and 4.2 reports regressions at the plant level. They show that the negative effect of plant output on the labor cost shares exceeds the positive effects of firm R&D and physical capital by a small yet significant amount. The rejection of homotheticity is probably due to errors in the plant level data. At this level, for example, we are unable to separate interplant transfers of materials within firms from other materials[21]. This could interact with plant specialization within firms. Smaller labor cost shares in large plants could signify larger transfers of materials from upstream plants to downstream "assembly" plants. Thus, doubling the output of every plant would leave cost shares the same, and yet shares of materials would be larger in these plants. In other words, smaller labor cost shares in larger plants could reflect plant specialization within firms rather than scale effects.

estimate of 10 states and 5 products.

[21] It is not possible to separate interplant transfers from other materials in the LRD.

To test this idea we estimate blue and white collar cost share equations at the state and firm level, thereby averaging out the effect of large plants. In effect, we construct state level manufacturing branches of the firm. Equations 4.3 and 4.4 display the results, which now support the hypothesis of homotheticity. The divergent plant and branch level findings in Table 4 could be due to plant specialization, or alternatively, to greater errors in output at the plant level[22]. In view of these ambiguities we choose the restricted form of costs (5) for the remainder of the paper. None of our conclusions on factor intensity or skill bias depend on this restriction, which simplifies the analysis and removes heteroscedasticity by eliminating size of plant.

B. Firm R&D and the Factor Intensity of Production

SUR estimates of the cost share systems are presented in Tables 5 through 8. All Tables include industry dummies as well as time trend to control for the effects of industry and time. The tables differ mainly in their specification of firm R&D. Table 5 uses total firm R&D, while Tables 6 and 7 break up firm R&D by state, and finally, Table 8 breaks up firm R&D by product.

We present results for the full set of variables in Table 5. Throughout we include industry dummies, time trend, factor prices, and controls for firm and industry size, in addition to R&D and capital. It is difficult to compare our results with those of other papers, since our specification differs from other applications of the Translog cost function. We break up labor into blue and white collar categories and treat capital and several forms of R&D as quasi-fixed[23]. However, the results seem internally consistent. For example, they imply negative own elasticities of substitution. At sample means the own elasticity of substitution for blue collar workers is $w^{wn} = w^{bl} \times \frac{E^{wh}}{{}^{bl}}$, while the elasticity for white collar workers is $s_{WW} = -6.5$. Blue and

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[22] Lagging plant output by one period made little difference to these results.

[23] Berndt and Wood (1975) for instance treat labor as an aggregate and capital as a variable input.

white collar workers are substitutes since $\boldsymbol{s}_{WB} = 1.6$ [24]. The implied elasticities for materials are $\boldsymbol{s}_{MM} = -0.2,\ \boldsymbol{s}_{MW} = 0.6,$ and $\boldsymbol{s}_{MB} = 0.8$. All three inputs are substitutes that are characterized by negative own price effects[25]. These results are insensitive to the use of current or lagged factor prices.

In addition to the above variables we include dummies for plant slowdown and plant birth. These are usually insignificant, though we find that plant birth significantly lowers the cost share of blue collar labor. We include number of firm plants as an indicator of size and diversity of the firm. The number of plants in the firm is associated with a decline in the labor cost shares, especially the white collar share. This effect could proxy for a variety of factors. It could stand for centralization of white collar workers in non-manufacturing facilities, for the dilution of the effects of firm R&D over heterogeneous products and processes, or even for vertical integration, and hence increasing interplant transfers of materials. However, we are unable to identify which of these causes dominates our results.

Our indicator of industry size is the weighted number of industry plants. This is the number of plants in other firms weighted by the uncentered correlation of the R&D of other firms with the parent firm's R&D (see equation (10) above). The effect of the number of industry plants again decreases the labor cost shares. Again it reflects a similar mix of causes: the

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[24] These calculations use the Translog formulas for the elasticities of substitution,

$$\boldsymbol{s}_{ii} = \frac{\boldsymbol{b}_{ii} + s_i^2 - s_i}{s_i^2},\ \boldsymbol{s}_{\mathrm{ij}} = \frac{\boldsymbol{b}_{ij} + s_i s_j}{s_i s_j}.$$

For a simple derivation see Hamermesh (1993).

[25] Global concavity cannot be guaranteed for the Translog cost function. But a representative finding is that 85% of all cases satisfied the criteria for concavity that enter Panel A, eq. 5.2 and 5.4. The criteria are that all three own elasticities of substitution $\boldsymbol{s}_{ii}$ be negative; that all three of the 2x2 determinants $\boldsymbol{s}_{ii}\boldsymbol{s}_{jj} - \boldsymbol{s}_{ij}$ be positive; and that the 3x3 determinant comprised of all the substitution elasticities be very close to zero (in our case the 3x3 determinant was bounded by ±1xE-9). For Panel B, eq. 5.2 and 5.4, 86% of all cases satisfied the concavity criteria. The primary reason for the failure of concavity was the small size of the white collar cost share in some plants. From fn. 24 this yields a positive value of $\boldsymbol{s}_{ww}$ if $\boldsymbol{b}_{ww}$ is positive. $\boldsymbol{s}_{ww}$ is positive in 12-13% of all cases.

dilution of the effect of industry R&D by the diversity of products, the growth of materials relative to sales due to plant specialization, and so on.

We turn next to the effects of R&D and physical capital on the cost shares. Throughout Table 5 we drop the industry spillover from odd numbered equations (5.1 and 5.3) and include it in even numbered ones (5.2 and 5.4). We follow this order of presentation in the other regression tables as well. Again results are about the same whether we use current or lagged plant output to compute the R&D and capital intensities.

Panel A presents findings for flows, Panel B the findings for stocks. Beginning with Panel A, R&D and physical capital increase the factor intensity of labor and decrease that of materials. The flow of firm R&D exhibits skill bias: its effect is smaller in the blue collar equation (5.1) than in the white collar equation (5.3) and the difference is significant at the one percent level. The effect of firm R&D diminishes when industry R&D is introduced and it is no longer significant in the blue collar equation (5.2). Industry R&D and plant level capital show little skill bias in Panel A.

Panel B of Table 5 introduces the stock of firm R&D over the previous five years in place of the flow. Results are similar to Panel A with two major exceptions: the industry spillover now exhibits significant skill bias that replaces the skill bias of firm R&D . This may reflect the greater importance of learning about the R&D of other firms in the larger enterprises represented in Panel B. More likely, it reflects transitory skill bias of current firm R&D, since current R&D is associated with larger numbers of white collar workers. In any event, the result points out that total firm R&D is not a consistent source of skill bias.

Tables 6 through 8 separate firm R&D into components that vary in their closeness to the plant. Since other variables behave similarly to Table 5, these tables are limited to findings for firm R&D, industry R&D, and the plant level capital stock.

Table 6 decomposes firm R&D into R&D conducted in the same state as the plant and R&D conducted in other states. Since R&D broken down in this way is not always positive we add a small positive number (0.1 thousand dollars) to R&D before taking logarithms. In addition we assign dummy variables equal to 1 when R&D is zero and 0 when it is positive. To indicate the presence of zero R&D, we interact the zero R&D dummies with the log of R&D. We refer to these variables hereafter as zero R&D interactions.

The format of Table 6 follows that of Table 5. Panel A reports flow estimates, while Panel B reports stock estimates. Consider Panel A. As in Table 5, the factor intensity of labor increases while that of materials diminishes in more R&D- and capital-intensive plants. There is some evidence of skill bias, since firm R&D in the same state as the plant is associated with significant increases in the white collar share, but not the blue collar share. R&D conducted by the firm in other states again raises the white collar share, and its effect is close to zero for the blue collar share. Skill bias does not seem to be geographically localized in Table 6 since both R&D in the same state and R&D in other states exhibit a similar degree of skill bias. The zero R&D interactions reveal that most of the skill bias of firm R&D disappears when firm R&D is zero. Industry R&D spillovers and plant capital stock are neutral by level of skill.

As before, the skill bias disappears when we turn to stocks of firm R&D in the same state as the plant and in other states. Panel B reports the findings. Any skill bias of firm R&D disappears, while the industry spillover and plant level capital now exhibit significant skill bias. However, we find evidence in Table 8 below that R&D in the same product area as the plant dominates the latter two variables with respect to skill bias.

We have already mentioned that the contemporaneous skill bias of R&D conducted in the same and other states may be due to the presence of R&D personnel among white collar workers the individual plants. In this view, the skill bias associated with current R&D picks up transitory R&D investment (see Bartel and Lichtenberg (1987)). This effect should disappear when we use stocks of R&D, as it in fact does. To investigate this further we acquired data on firm R&D carried out in separate laboratories in particular states by our chemical firms, in an effort to distinguish separately conducted R&D from R&D in the plant itself. Auxiliary establishment data are available for the Census of Manufacturing years 1977, 1982, and 1987 for about fifty percent of the plants. As a result sample size is much smaller than before.

The findings are contained in Table 7. Consider Panel A first: holding the log of R&D conducted in separate establishments constant, R&D conducted in the same state has a *larger* effect on the white collar share than in Table 6 (0.010 versus 0.006); as there, the effect on the blue collar share is essentially zero. Consistent with this, the effect of R&D conducted in separate laboratories *decreases* the white collar cost share by –0.004.

These results are in fact consistent with the presence of *current* R&D personnel among white collar workers in the same state. First, R&D in the same state and R&D conducted in separate laboratories are positively correlated. Second, the number of R&D personnel included among white collar employees in manufacturing plants is negatively correlated with the amount of R&D in separate laboratories. It follows that our not controlling for separately conducted R&D in Table 6 *lowers* the effect of same state R&D compared with Table 7[26]. The *full* effect of "double counting" of R&D workers causes the white collar coefficient to be 0.010 (Table 7) rather than 0.006 (Table 6).

However, as in Table 6, the stock results of Table 7 (Panel B) are different from the flow results. The effect of local firm R&D on the white collar share is exactly the same as in Table 6, and auxiliary R&D is insignificant. The stock results suggest in a different way that there is a small degree of "double counting" in the flow results. In this interpretation the true effect of local firm R&D is 0.004 rather than 0.006, and the skill bias associated with firm R&D is transitory in Panel A[27]. Together Tables 6 and 7 suggest that firm R&D broken up by the same state as the plant is not a strong or consistent source of skill bias in the long run.

This assessment changes drastically when we decompose firm R&D into firm R&D in the same and other products than the plant. As in previous tables, we introduce zero R&D interactions to capture the presence of zero R&D in the same and other products. But because firm R&D in other products is never zero no such interaction appears in Table 8.

Table 8 shows that R&D in the same product generates skill bias with far greater consistency than other types of firm R&D. This finding holds up whether we use the flow or the stock of R&D. While it is certainly possible that some of the skill bias is due to the presence of R&D personnel in the individual plant, this "double counting" problem is probably unimportant for two reasons. First, we found in Tables 6 and 7 that the results for the *stock* of same state R&D did not change when we controlled for the amount of R&D conducted in separate laboratories. Second, while we cannot perform a similar check for same product R&D, the fact that stock and flow results are about the same in Table 8 suggests that double counting of *current* R&D, the only significant bias of this kind in Table 6, is unimportant here.

The skill bias of firm R&D in the same product remains whether or not we include the R&D spillover. However, firm R&D in the same product is factor saving for blue collar workers once the R&D spillover is included. It is interesting that, unlike Tables 5, 6, and 7, the industry R&D spillover and plant level capital no longer exhibit a significant skill bias. In this sense the

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[26] Use the omitted variable formula in regression analysis to prove this result.
[27] For a related finding that applies to productivity of French and American manufacturing firms, see Hall and

skill bias effect of firm R&D in the same product dominates any purported skill bias of the other variables. Furthermore, firm R&D in other products is insignificant for both skill classes in this table. These patterns in the results suggest that skill bias is “localized” in *portions* of firm R&D that are in the same product, and thus targeted on particular plants.

V. Discussion of the Findings

Previous findings in this paper have compared the effects of R&D and capital *across* the factors of production. These results while informative, give little sense of the comparative importance of the different variables for factor intensity. They do not provide clear comparisons across *variables*. This is because the regression coefficients show changes in cost shares with respect to one percent changes in the intensities rather than unit changes. To see this, use (5) to write out the regression coefficient for the jth R&D intensity:

$$\boldsymbol{b}_{iR_j} = \frac{\partial s_i}{\partial \ell n \left(\frac{R_j}{q}\right)} = \frac{\partial s_i}{\partial \left(\frac{R_j}{q}\right)} \left(\frac{R_j}{q}\right) \quad . \tag{11}$$

The *derivative* of the cost share evaluated at sample means is then

$$c_{iR_j} \equiv \frac{\partial s_i}{\partial \left(\frac{R_j}{q}\right)} = \frac{\boldsymbol{b}_{iRj}}{\left(\frac{\overline{R}_j}{\overline{q}}\right)} , \tag{12}$$

in which $\overline{R}_j/\overline{q}$ is the sample mean intensity[28].

We use (12) to compute *derivatives* of the cost shares with respect to the R&D and capital intensities. Calculations of c_{iR_j} are shown in Table 9 based on Tables 6 and 8. The derivatives indicate that *per unit of R&D intensity*, most of the effect on the factor intensity of labor is due to plant level capital. Firm R&D has the second largest unit effect, and the R&D

Mairesse (1995). They also find that current R&D effects on productivity exceed lagged R&D effects.

[28] The weighted mean intensity is the ratio of mean R&D to mean output. The unweighted mean intensity is the

spillover has the smallest effect. But the largest unit effect on the *skill bias* is due to firm R&D in the same product. Once this variable is included there is no significant factor bias of other firm R&D, industry R&D, or plant level capital.

In an earlier paper, Adams and Jaffe (1996) present evidence that the effect of firm R&D on total factor productivity fades out with increasing geographic and technological distance from the plant[29]. Careful scrutiny of Table 9 shows that the effect of firm R&D on factor intensity of particular inputs also fades out with distance from the plant. To see this, compare rows 1 and 2, 5 and 6, 9 and 10, and 13 and 14 of Table 9. In each of these comparisons the unit effect of a change in R&D intensity in other states or other products is smaller *in absolute value* than the unit effect of R&D in the same state or the same product. The reason why we stipulate absolute values of course, is that R&D can be factor saving in the present paper.

VI. Conclusion

This paper has presented evidence on the determinants of factor intensity and skill bias at the plant level using a sample of plants owned by chemical firms. Using evidence on the structure of firm R&D, and holding constant a measure of the industry R&D spillover as well as plant level physical capital, we have found the following results. First, we find that R&D and physical capital are associated with increases in the factor intensity of labor and decreases in the factor intensity of materials. Second, we find that total firm R&D, the industry R&D spillover, and plant level physical capital are not consistently associated with skill bias. Third, we find that firm R&D in the same product area as the plant is primarily responsible for skill bias. Neither industry R&D nor plant level capital contribute to skill bias in the presence of firm R&D in the

mean of the individual ratios. The weighted intensity gives more influence to plants with larger outputs. Since both R&D and output are measured in thousands of 1987 dollars, the intensity is dimensionless.

[29] For more on this issue see Klette (1996).

same product. All told, the findings suggest that skill bias is governed by *portions* of the firm's R&D program targeted on particular plant, rather than transmitted through capital or general firm and industry know-how.

The analysis could be extended in several directions. First, we could expand the coverage to more industries, given the necessary resources to do so. Second, we could include the cost function in the estimation procedures, although this is subject to the consistency critique of McElroy (1987). In related work we find evidence of falling average costs that are partly due to firm R&D. This is consistent with the internal scale economies emphasized by the endogenous growth literature (Romer (1990)). Third, we could explore the endogeneity of firm investments in R&D and physical capital in a more complete model of the firm's decision-making process. This would be a major step towards unifying the determinants of factor intensity and skill bias with the determinants of investments in capital and new technology.

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Table 1
Plant Level Variable Cost Shares
by Numbers of Manufacturing Plants in the Firm:
Chemical Firms: 1974-1988

Number of Plants per Firm	Number of Plant-Years	Cost Shares	
		Blue Collar Labor	White Collar Labor
1-10	2037	0.13	0.13
11-20	2873	0.15	0.13
21-40	4354	0.16	0.10
41-70	3463	0.13	0.08
71+	5862	0.15	0.10

Notes. A plant-year is an observation on a particular plant in a particular year. The cost shares are the expenditures on blue and white collar labor divided by all variable costs: the expenditures on both forms of labor and the materials, energy, and services aggregate.

Table 2
Plant Level Variable Cost Shares by Industry Group: Chemical Firms, 1974-1988

Product Group	Number of Plant-Years	Cost Shares	
		Blue Collar Labor	White Collar Labor
Food	1023	0.09	0.04
Textiles and Apparel	531	0.24	0.08
Wood and Paper	689	0.15	0.08
All Chemicals	**11209**	**0.12**	**0.10**
Organic and Inorganic Chemicals	4785	0.11	0.10
Plastics, Resins, and Fibers	1207	0.10	0.06
Drugs and Agricultural Chemicals	2096	0.15	0.16
Soaps, Paints, and Miscellaneous Chemicals	3112	0.07	0.09
Petroleum and Coal	305	0.05	0.03
Rubber and Plastics	1026	0.21	0.10
Stone, Clay, and Glass	423	0.22	0.12
Metals	899	0.21	0.10
Machinery	710	0.24	0.18
Electrical Equipment	660	0.22	0.15
Instruments	1118	0.25	0.21

Notes. A plant-year is an observation on a particular plant in a particular year. The cost shares are the expenditures on blue and white collar labor divided by all variable costs: the expenditures on both forms of labor and on the aggregate of materials, energy, and services.

Table 3
Means and Standard Deviations of the R&D,
Capital, and Output Variables:
Chemical Firms, 1974-1988

Variable	Mean	Standard Deviation
Panel A. Firm R&D Flow Data (N=18589)		
Flow of Total Firm R&D	164,179	240,458
Flow of Firm R&D in the Same State	12,923	47,844
Flow of Firm R&D in Other States	151,256	189,438
Flow of Firm R&D in the Same Product	24,306	46,106
Flow of Firm R&D in Other Products	139,872	178,075
Industry R&D Spillover	1,211,255	510,985
Plant Capital Stock	34,884	89,894
Plant Output	73,273	145,711
Panel B. Firm R&D Stock Data (N=9559)		
Stock of Total Firm R&D	575,912	699,798
Stock of Firm R&D in the Same State	45,550	141,811
Stock of Firm R&D in Other States	530,363	678,085
Stock of Firm R&D in the Same Product	91,942	156,878
Stock of Firm R&D in Other Products	484,916	618,815
Industry R&D Spillover	1,354,757	555,335
Plant Capital Stock	37,492	95,959
Plant Output	82,061	158,441

Notes. All variables are in thousands of 1987 dollars.

Table 4
Homotheticity Tests of Translog Factor Demands
at the Plant and Firm Levels: Chemical Firms, 1974-1988
(t-Statistics in Parentheses)

Variable	Plant Level Cost Shares		State and Firm Level Cost Shares	
	Blue Collar Labor	White Collar Labor	Blue Collar Labor	White Collar Labor
	Eq. 4.1	Eq. 4.2	Eq. 4.3	Eq. 4.4
Panel A. Flow of Firm R&D				
β_{iR} : Log (Flow of firm R&D)	0.001 (1.6)	0.006 (9.9)	0.003 (3.3)	0.004 (4.9)
β_{iK} : Log (Physical capital)	0.017 (21.2)	0.018 (21.8)	0.020 (18.1)	0.015 (11.7)
β_{iq} : Log (output)	-0.021 (25.5)	-0.031 (34.3)	-0.026 (-20.5)	-0.020 (-14.6)
$\beta_{iR} + \beta_{iK} + \beta_{iq}$ (F Statistic for $\beta_{iR} + \beta_{iK} + \beta_{iq}=0$)	-0.003 (31.0*)	-0.007 (71.0*)	-0.003 (10.2*)	-0.001 (1.9)
Panel B. Stock of Firm R&D				
β_{iR} : Log (Stock of Firm R&D)	0.003 (3.0)	0.005 (4.7)	0.003 (2.9)	0.004 (3.6)
β_{iK} : Log (Physical capital)	0.014 (13.1)	0.019 (16.0)	0.018 (12.3)	0.016 (9.8)
β_{iq} : Log (Output)	-0.018 (-5.4)	-0.030 (-24.5)	-0.023 (-13.7)	-0.022 (-12.3)
$\beta_{iR} + \beta_{iK} + \beta_{iq}$ (F Statistic for $\beta_{iR} + \beta_{iK} + \beta_{iq}=0$)	-0.001 (1.9)	-0.006 (46.7*)	-0.002 (0.8)	-0.002 (2.0)

Notes. An * means that the F-statistic for $\beta_{iR} + \beta_{iK} + \beta_{iq}=0$ is significantly different from zero at the 1% level.

Table 5
SUR Estimates of Plant Level Translog Factor Demands:
Chemical Firms, 1974-1988
(t-Statistics in Parentheses)

Variable	Cost Shares			
	Blue Collar Labor		White Collar Labor	
	Eq. 5.1	Eq. 5.2	Eq. 5.3	Eq. 5.4
Panel A. Flow of Firm R&D				
Industry dummies, time trend included	Yes	Yes	Yes	Yes
Log (Relative white collar labor price)	0.009 (1.6)	0.007 (1.2)	0.025 (3.8)	0.023 (3.6)
Log (Relative blue collar labor price)	0.011 (1.7)	0.009 (1.4)	0.009 (1.7)	0.007 (1.2)
Plant slowdown	0.013 (2.2)	0.010 (1.8)	-0.008 (-1.1)	-0.011 (-1.7)
Plant birth	-0.023 (-2.8)	-0.026 (-3.3)	0.007 (0.8)	0.003 (0.4)
Log (Number of plants in the firm)	-0.006 (-6.9)	-0.003 (-3.3)	-0.021 (-22.6)	-0.017 (-16.9)
Log (Number of plants in the Industry)		-0.014 (-7.4)		-0.009 (-4.4)
Log (Flow of firm R&D/output)	0.003 (8.4)	0.000 (0.4)	0.010* (23.7)	0.006** (9.2)
Log (Physical capital/output)	0.016 (21.1)	0.017 (21.4)	0.018 (21.7)	0.019 (22.0)
Log (Industry R&D spillover/output)		0.004 (6.9)		0.006 (8.2)
Number of observations	18583			
Panel B. Stock of Firm R&D				
Industry dummies, time trend included	Yes	Yes	Yes	Yes
Log (Relative white collar labor price)	0.016 (2.2)	0.013 (1.9)	0.032 (3.6)	0.027 (3.1)
Log (Relative blue collar labor price)	-0.005 (-0.6)	-0.008 (-0.9)	0.016 (2.2)	0.013 (1.9)

Table 5
SUR Estimates of Plant Level Translog Factor Demands:
Chemical Firms, 1974-1988
(t-Statistics in Parentheses)

Variable	Cost Shares			
	Blue Collar Labor		White Collar Labor	
	Eq. 5.1	Eq. 5.2	Eq. 5.3	Eq. 5.4
Panel B. Stock of Firm R&D (cont.)				
Plant slowdown	0.021 (2.7)	0.021 (2.6)	-0.009 (-1.0)	-0.011 (-1.2)
Plant birth	0.008 (0.6)	0.005 (0.4)	-0.005 (-0.4)	-0.009 (-0.6)
Log (Stock of Firm R&D/output)	0.004 (6.4)	0.002 (2.3)	0.010* (15.8)	0.005 (4.6)
Log (Physical capital/output)	0.014 (13.6)	0.014 (13.2)	0.018* (15.7)	0.019** (16.0)
Log (Industry R&D Spillover/output)		0.002 (2.3)		0.006** (6.3)
Log (Number of plants in the firm)	-0.008 (-6.8)	-0.006 (-4.7)	-0.022 (-17.2)	-0.018 (-12.4)
Log (Weighted Number of plants in the Industry)		-0.015 (-5.3)		-0.009 (-3.1)
Number of observations	9556			

Notes. *R&D or capital coefficient in 5.3 is significantly different from the coefficient in 5.1 at the 1% level.
** R&D or capital coefficient in 5.4 is significantly different from the coefficient in 5.2 at the 1% level.

Table 6
SUR Estimates of Plant Level Translog Factor Demands,
Geographic Decomposition of R&D: Chemical Firms, 1974-1988
(t-Statistics in Parentheses)

Variable	Cost Shares			
	Blue Collar Labor		White Collar Labor	
	Eq. 6.1	Eq. 6.2	Eq. 6.3	Eq. 6.4
Panel A. Flow of Firm R&D in the Same State as the Plant and in Other States.				
Log (Flow of firm R&D in the same state/output)	0.001 (1.7)	-0.001 (-1.1)	0.006* (12.6)	0.005** (8.9)
Same state R&D dummy [a] × Log (Flow of firm R&D in the same state/output)	0.000 (0.2)	0.001 (2.8)	-0.003 (-7.5)	-0.002 (-4.4)
Log (Flow of firm R&D in other states/output)	0.002 (6.0)	-0.000 (-0.8)	0.007* (17.0)	0.004** (6.5)
Other state R&D dummy [b] × Log (Flow of firm R&D in other states/output)	-0.002 (-3.8)	0.001 (1.0)	-0.008 (-15.9)	-0.005 (-8.6)
Log (Physical Capital/Output)	0.016 (21.1)	0.017 (21.4)	0.017 (20.6)	0.017 (20.8)
Log (Industry R & D Spillover/Output)		0.005 (8.1)		0.006 (9.2)
Number of observations			18583	
Panel B. Stock of Firm R&D in the same state as the plant and in other states.				
Log (Stock of firm R&D in the same state/output)	0.002 (4.1)	0.002 (3.2)	0.004* (7.8)	0.003 (5.9)
Same state R&D dummy [a] × Log (Stock of firm R&D in the same state/output)	-0.001 (-2.5)	-0.001 (-1.6)	-0.002 (-3.4)	-0.001 (-1.7)
Log (Stock of firm R&D in other states/output)	0.002 (4.5)	0.001 (1.2)	0.007* (11.3)	0.001 (1.4)
Other state R&D dummy [b] × Log (Stock of firm R&D in other states/output)	-0.002 (-1.9)	-0.000 (-0.0)	-0.009 (-9.1)	-0.003 (-2.8)
Log (Physical Capital/Output)	0.014 (12.8)	0.014 (12.9)	0.018* (15.3)	0.018** (15.6)
Log (Industry Spillover/Output)		0.002 (2.6)		0.008** (8.3)
Number of observations			9556	

Notes. *R&D or capital coefficient in 6.3 is significantly different from the coefficient in 6.1 at the 1% level. ** R&D or capital coefficient in 6.4 is significantly different from the coefficient in 6.2 at the 1% level. [a] Same state R&D dummy equals 1 if firm R&D in the same state as the plant equals zero, and 0 if same state R&D is positive. [b] Other state R&D dummy equals 1 if firm R&D in other states equals zero, and 0 if R&D conducted in other states is positive.

Table 7
SUR Estimates of Plant Level Factor Demands,
Geographic Decomposition of R&D with R&D Separately Conducted in Auxiliaries:
Chemical Firms, Census Years 1977, 1982, and 1987
(t-statistics in Parentheses)

Variable	Cost Shares			
	Blue Collar Labor		White Collar Labor	
	Eq. 7.1	Eq. 7.2	Eq. 7.3	Eq. 7.4
Panel A. Flow of Firm R&D in the same state as the plant and in other states, holding constant Auxiliary R&D conducted separately in the same state.				
Log (Flow of Firm R&D in the same state/output)	-0.000 (-0.1)	-0.000 (-0.3)	0.010* (5.8)	0.010** (5.4)
Same state R&D dummy [a] × Log (Flow of Firm R&D in the same state/output)	0.001 (0.3)	0.001 (0.6)	-0.009 (-5.7)	-0.008 (-5.2)
Log (Flow of Firm R&D in other states/output)	-0.000 (-0.1)	-0.001 (-0.8)	0.006* (4.7)	0.004 (2.6)
Other state R&D dummy [b] × Log (Flow of Firm R&D in other states/output)	0.001 (0.7)	0.002 (1.3)	-0.007 (-4.8)	-0.006 (-3.4)
Log (Flow of Auxiliary Firm R&D conducted separately in the same state)	0.001 (0.7)	0.001 (0.4)	-0.004 (-2.1)	-0.004 (-2.2)
Same state auxiliary R&D dummy [c] × Log (Flow of Auxiliary Firm R&D conducted separately in the same state)	0.000 (0.1)	0.000 (0.3)	0.003 (2.0)	0.003 (2.1)
Log (Physical Capital/Output)	0.017 (7.5)	0.017 (7.6)	0.014 (5.5)	0.014 (5.6)
Log (Industry R&D Spillover/output)		0.002 (1.3)		0.003 (1.6)
Number of observations	1838			
Panel B. Stock of Firm R&D in the same state as the plant and in other states, holding constant Auxiliary R&D conducted separately in the same state.				
Log (Stock of Firm R&D in the same state/output)	0.003 (1.8)	0.003 (1.8)	0.004 (2.4)	0.004 (2.1)
Same state R&D dummy [a] × Log (Stock of Firm R&D in the same state/output)	-0.002 (-1.6)	-0.002 (-1.5)	-0.003 (-1.6)	-0.002 (-1.3)
Log (Stock of Firm R&D in other states/output)	0.001 (0.8)	0.002 (0.7)	0.007* (4.5)	0.003 (1.5)

Table 7
SUR Estimates of Plant Level Factor Demands,
Geographic Decomposition of R&D with R&D Separately Conducted in Auxiliaries:
Chemical Firms, Census Years 1977, 1982, and 1987
(t-statistics in Parentheses)

Variable	Cost Shares			
	Blue Collar Labor		White Collar Labor	
	Eq. 7.1	Eq. 7.2	Eq. 7.3	Eq. 7.4
Panel B. Stock of Firm R&D in the same state as the plant and in other states, holding constant Auxiliary R&D conducted separately in the same state. (cont.)				
Other state R&D dummy[b] × Log (Stock of Firm R&D in other states/output)	-0.001	-0.001	-0.006	-0.002
	(-0.4)	(-0.3)	(-2.3)	(-0.6)
Log (Flow of Auxiliary Firm R&D conducted separately in the same state)	-0.004	-0.004	0.003	0.003
	(-1.8)	(-1.8)	(1.3)	(1.1)
Same state auxiliary R&D dummy[c] × Log (Flow of Auxiliary Firm R&D conducted separately in the same state)	0.004	0.004	-0.003	-0.003
	(2.4)	(2.4)	(-1.5)	(-1.3)
Log (Physical Capital/Output)	0.016	0.016	0.016	0.017
	(6.0)	(5.8)	(5.3)	(5.5)
Log (Industry R&D Spillover/output)		-0.000		0.006
		(-0.1)		(2.4)
Number of Observations	1309			

Notes. Data are limited to the years 1977, 1982, and 1987. All equations include dummies for 1977 and 1982, and industry dummies. *R&D or capital coefficient in 7.3 is significantly different from the coefficient in 7.1 at the 1% level. ** R&D or capital coefficient in 7.4 is significantly different from the coefficient in 7.2 at the 1% level.
[a] Same state R&D dummy equals 1 if firm R&D in the same state as the plant equals zero, and 0 if same state R&D is positive. [b] Other state R&D dummy equals 1 if firm R&D in other states equals zero, and 0 if R&D in other states is positive. [c] Same state auxiliary dummy equals 1 if firm R&D conducted separately in auxiliary R&D laboratories equals zero, and 0 if separately conducted R&D is positive.

Table 8
SUR Estimates of Translog Factor Demands,
Effects of Lagged Stocks of R&D and R&D Spillovers,
Product Decomposition of R&D: Chemical Firms, 1974-1988
(t-Statistics in Parentheses)

Variable	**Cost Shares**			
	Blue Collar Labor		**White Collar Labor**	
	Eq. 8.1	**Eq. 8.2**	**Eq. 8.3**	**Eq. 8.4**
Panel A. Flow of Firm R&D in the same product as the plant and in other products.				
Log (Flow of Firm R&D in the same product/output)	0.000 (0.3)	-0.004 (-7.3)	0.009* (18.7)	0.005** (8.5)
Same product R&D dummy [a] × Log (Flow of Firm R&D in the same product /output)	0.001 (1.9)	0.004 (9.0)	-0.006 (-14.9)	-0.003 (-6.2)
Log (Flow of Firm R&D in other products/output)	0.001 (4.0)	0.000 (0.2)	0.002 (7.1)	0.001 (2.7)
Log (Physical Capital/Output)	0.017 (22.2)	0.017 (22.5)	0.018 (21.7)	0.018 (21.9)
Log (Industry R&D Spillover/output)		0.007 (12.4)		0.007 (11.7)
Number of observations	18583			
Panel B. Stock of Firm R&D in the same product as the plant and in other products.				
Log (Stock of Firm R&D in the same product/output)	0.000 (0.5)	-0.002 (-3.2)	0.008* (13.5)	0.005** (7.3)
Same product R&D dummy [a] × Log (Stock of Firm R&D in the same product/output)	0.001 (1.4)	0.003 (4.9)	-0.008 (-11.9)	-0.005 (-6.4)
Log (Stock of firm R&D in other products/output)	0.001 (3.5)	0.001 (1.3)	0.001 (2.8)	-0.001 (-1.0)
Log (Physical Capital/Output)	0.014 (13.5)	0.015 (13.7)	0.018 (15.7)	0.018 (15.9)
Log (Industry R&D Spillover/output)		0.005 (6.1)		0.007 (9.0)
Number of observations	9556			

Notes. *R&D or capital coefficient in 8.3 is significantly different from the coefficient in 8.1 at the 1% level. ** R&D or capital coefficient in 8.4 is significantly different from the coefficient in 8.2 at the 1% level. [a] Same product R&D dummy equals 1 if stock of firm R&D in the same product as the plant is equal to zero, and 0 if same product R&D is positive.

Table 9
Derivative Effects of R&D and Physical Capital on the Labor Cost Shares

Variable	Table, Panel, Specification	Effect on Blue Collar Share	Effect on White Collar Share
Panel A. R&D Flow Sample			
1. Flow of Firm R&D in Same State	Table 6, Panel A, Eq. 6.2, 6.4	-0.0057#	0.0284**
2. Flow of Firm R&D in Other States	“	0.0000#	0.0019**
3. Industry R&D Spillover	“	0.0003	0.0004
4. Plant Capital Stock	“	0.0357	0.0357
5. Flow of Firm R&D in Same Product	Table 8, Panel A, Eq. 8.2, 8.4	-0.0121	0.0151**
6. Flow of Firm R&D in Other Products	“	0.0000#	0.0005
7. Industry R&D Spillover	“	0.0004	0.0004
8. Plant Capital	“	0.0357	0.0378
Panel B. R&D Stock Sample			
9. Stock of Firm R&D in Same State	Table 6, Panel B, Eq. 6.2, 6.4	0.0036	0.0054
10. Stock of Firm R&D in Other States	“	0.0002#	0.0002#
11. Industry R&D Spillover	“	0.0001	0.0005**
12. Plant Capital Stock	“	0.0306	0.0394**
13. Stock of Firm R&D in Same Product	Table 8, Panel B, Eq. 8.2, 8.4	-0.0018	0.0045**
14. Stock of Firm R&D in Other Products	“	0.0001#	-0.0001#
15. Industry R&D Spillover	“	0.0003	0.0004
16. Plant Capital Stock	“	0.0372	0.0394

Notes. Derivative effects are small changes in the cost shares divided by small changes in the R&D and capital intensities. See (13) of the text. # Derivative effect is *not* significant at the 1% level. ** Difference in derivative effects for blue and white collar labor is significant at the 1% level.